

# Transfer Learning-based Deep Neural Network for Early-Stage Cervical Cancer Prediction

Dr. Raghavendra Patidar<sup>1</sup>, Akanksha Tiwari<sup>2</sup>, Nishant Kumar<sup>3</sup>, Cijin K Paul<sup>4</sup>, Dr. Shipra Srivastava<sup>5</sup>, Sudhir Goswami<sup>6</sup>

<sup>1</sup>Professor, Department of Computer Science & Applications,  
Vivekananda Global University, Jaipur, Rajasthan, India  
Email: raghavendrapatidar@gmail.com

<sup>2</sup>Assistant Professor, Department of Electronics and Communication Engineering,  
Feroze Gandhi Institute of Engineering and Technology, Raebareli, UP, India  
Email: akanksha411@gmail.com

<sup>3</sup>Assistant Professor, Department of Mechanical Engineering,  
Government Engineering College, West Champaran, Bihar, India  
Email: bksism2013@gmail.com

<sup>4</sup>Assistant Professor, Department of Computer Science,  
Union Christian College, Aluva, Kerala, India  
Email: cijinkpaul@uccollege.edu.in

<sup>5</sup>Associate professor, Electronics and Communication Engineering,  
Krishna Institute of Engineering and Technology (KIET), Ghaziabad, UP, India  
Email: shipra.srivastava@kiet.edu

<sup>6</sup>Assistant Professor, Department of Information Technology,  
Rajkiya Engineering College Bijnor, UP, India  
Email: sudhir.it@recb.ac.in

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## ABSTRACT

Cervical cancer remains a significant global health challenge, where early detection of precancerous lesions is essential for improving survival rates. This study proposes a transfer learning-based deep neural network for early-stage cervical cancer prediction using the ResNet50 model. The approach leverages pre-trained weights to extract discriminative features from cervical cell images, followed by customized classification layers for accurate diagnosis. Image preprocessing techniques such as resizing, normalization, and data augmentation are applied to enhance model performance and generalization. The proposed model is evaluated against baseline methods including basic CNN, Support Vector Machine, Random Forest, and K-Nearest Neighbors, and demonstrates superior performance with an accuracy of 96.85%, precision of 96.20%, recall of 96.00%, and an F1-score of 96.10%. These results confirm the effectiveness of transfer learning in medical image analysis and highlight the potential of the proposed system to support automated, reliable, and early detection of cervical cancer.

**Keywords:** ResNet50, CNN, Machine Learning, Cervical Precancer Detection, Convolutional Neural Network (CNN), Deep Learning.

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## INTRODUCTION

Cervical cancer remains one of the leading causes of cancer-related mortality among women worldwide, particularly in low- and middle-income countries where access to early screening is limited. According to the World Health Organization, early detection of cervical abnormalities significantly improves survival rates and reduces disease progression [12-13]. Traditional screening techniques such

as Pap smear tests and colposcopy rely heavily on expert interpretation, which can be time-consuming, subjective, and prone to diagnostic variability. With the increasing availability of medical imaging data, there is a growing need for automated and reliable systems that can assist clinicians in detecting early-stage cervical cancer with higher accuracy and efficiency [14].

In recent years, deep learning, a subfield of Artificial Intelligence [15], has demonstrated remarkable success in medical image analysis. Among various architectures, the ResNet50 model has emerged as a powerful tool due to its ability to learn deep hierarchical features while mitigating issues such as vanishing gradients through residual connections [16]. ResNet50, pre-trained on large-scale datasets, can be effectively adapted using transfer learning techniques to analyze cervical cell images and identify subtle patterns associated with early malignancy. Its depth and robustness make it particularly suitable for handling complex variations in medical imaging data.

The application of a ResNet50-based deep neural network for early-stage cervical cancer prediction offers significant potential to enhance diagnostic accuracy and support clinical decision-making. By leveraging transfer learning, the model can utilize prior knowledge and adapt to domain-specific datasets, even when labeled medical data is limited [17]. This approach not only reduces computational cost and training time but also improves generalization performance. Consequently, integrating ResNet50 into cervical cancer screening frameworks can facilitate early intervention, reduce diagnostic errors, and contribute to improved patient outcomes, marking a crucial advancement in intelligent healthcare systems.

## 1. REVIEW OF LITERATURE

The existing body of research on cervical precancer detection highlights the growing importance of automated and intelligent diagnostic systems to overcome the limitations of conventional screening techniques. Early studies primarily focused on improving cell segmentation using deep learning architectures. For instance, deep segmentation networks have demonstrated significant improvements in accurately identifying and isolating cervical cells in annotated Pap smear datasets, although these approaches are highly dependent on the availability of well-labeled data [1]. To enhance overall diagnostic performance, researchers have integrated segmentation with classification models. An ensemble framework combining segmentation techniques with CNN classifiers on datasets such as Herlev and SIPaKMeD has shown improved screening accuracy, although challenges such as cell overlap and staining variations still persist [2].

Further advancements have explored ensemble learning strategies to improve robustness and classification performance. Fuzzy rank-based CNN ensembles applied to the Herlev dataset have shown better performance compared to single CNN models, though they often lack interpretability [3], [20]. Comprehensive surveys of deep learning techniques indicate that combining segmentation, transfer learning, and ensemble methods yields the best

results in cervical cancer detection tasks; however, the limited size of medical datasets remains a major constraint affecting model generalization [4]. In addition, transfer learning approaches utilizing multiple pre-trained CNN architectures have achieved competitive accuracy even without explicit segmentation, although segmentation becomes beneficial when dealing with noisy or complex images [5], [22].

Recent research trends emphasize hybrid and advanced deep learning models that integrate multiple methodologies. CNN ensembles combining architectures such as SqueezeNet, AlexNet, and custom CNNs have demonstrated improved multi-class classification performance on datasets like SIPaKMeD and Herlev, albeit with increased computational complexity [6]. Moreover, the integration of CNNs with Transformer architectures has enabled the capture of global contextual features, improving robustness against occlusion and overlapping cells, though such models require large-scale datasets or extensive pretraining [7]. Hybrid approaches that incorporate fuzzy distance-based ensembles with deep learning have further enhanced sensitivity by combining interpretable features with high-level representations [8]. Additionally, statistical regression and traditional machine learning models, such as logistic regression and decision trees, continue to play a vital role, particularly when image data is limited, due to their interpretability and stable performance on clinical tabular datasets [9]. Collectively, these studies demonstrate that hybrid frameworks combining deep learning with statistical and ensemble techniques offer a promising direction for achieving accurate, robust, and scalable cervical precancer detection systems.

## 2. DATASET

The dataset used for this study comprises benchmark dataset of 3000 cervical images collected from HPV-positive women, with each patient represented by three distinct views of the cervix. These images are captured following the application of various diagnostic substances to aid in the identification of potential precancerous or cancerous lesions. The dataset includes three types of images for each patient:

1. *NATIVE*: This view shows the cervix in its natural state, before the application of any diagnostic substances, providing a baseline for visual assessment.
2. *VIA (Visual Inspection with Acetic Acid)*: This image is taken after applying acetic acid to the cervix. Acetic acid highlights abnormal epithelial changes, which appear as white patches, allowing

the identification of potential precancerous regions.

3. *VILI (Visual Inspection with Lugol's Iodine)*: This image is captured after Lugol's iodine is applied. Normal squamous epithelium absorbs iodine and stains brown, whereas abnormal or precancerous areas remain unstained or appear yellow, assisting in lesion detection.

The dataset consists of detailed colposcopic and clinical information for HPV-positive women, structured across multiple fields. Each entry includes general assessments, normal and abnormal findings, lesion characteristics (location, size, margins, vessel patterns), and

transformations observed in the cervix, along with responses to diagnostic substances such as acetic acid (Aceto Uptake) and Lugol's iodine (Iodine Uptake). Additional fields capture the visibility of the squamocolumnar junction, transformation zone, epithelial types, and pregnancy-related changes. The dataset also includes Swede scores, provisional diagnoses, recommended management, and histopathology-confirmed outcomes, providing a comprehensive resource for training and validating automated cervical precancer detection systems. By combining image-based observations with clinical and histological data, the dataset enables models to learn both morphological and diagnostic patterns critical for accurate classification.

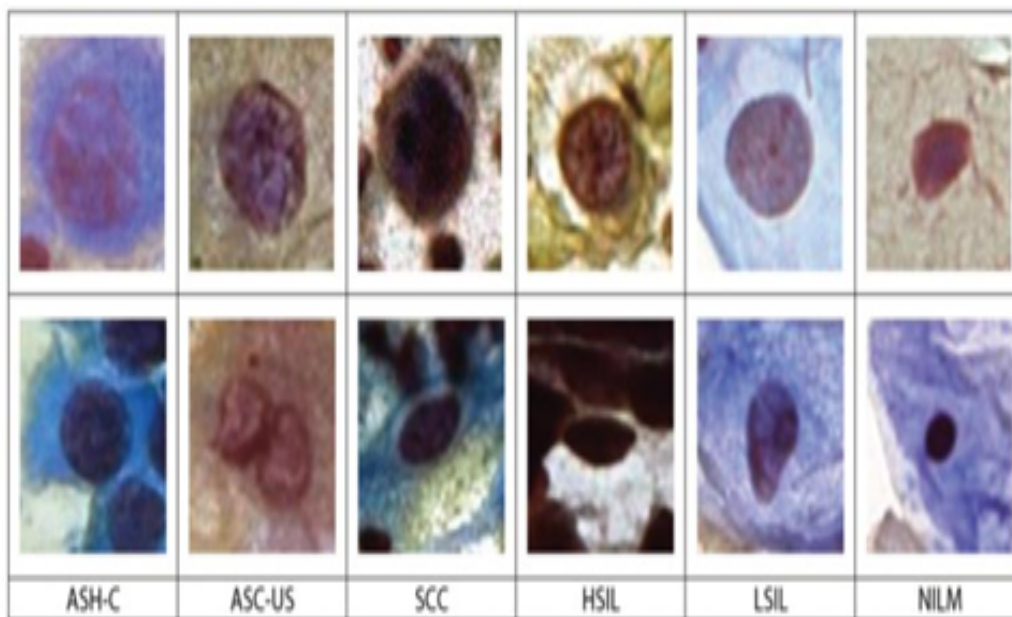


Figure 1. Sample images from the benchmark dataset

Figure 2. Sample images from the benchmark dataset illustrating the visual diversity and variations present across different cervical types. These images demonstrate differences in texture, color intensity, illumination, and structural patterns, which are critical for accurate feature extraction and classification during model training and evaluation.

### 3. PROPOSED SYSTEM MODEL AND ALGORITHM

The proposed system model presents an automated and intelligent framework for the early-stage detection of cervical cancer using a deep learning approach based on

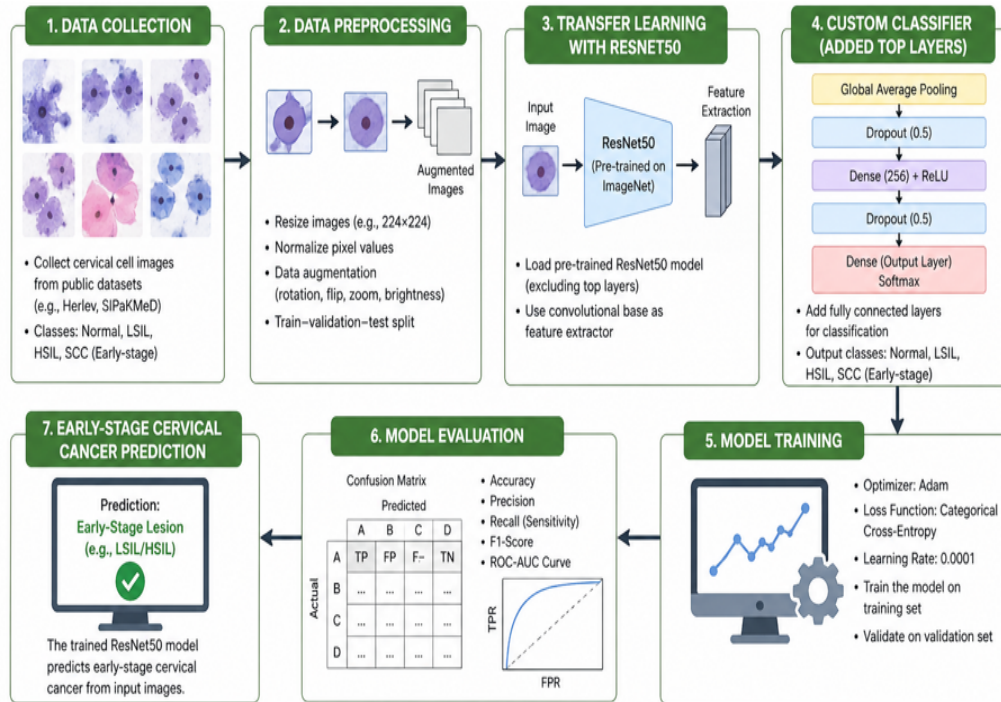
ResNet50. The system leverages transfer learning to effectively analyze cervical cell images and identify subtle abnormalities that may indicate the onset of cancer. By integrating image preprocessing, deep feature extraction, and classification into a unified architecture, the model aims to improve diagnostic accuracy while reducing reliance on

manual screening procedures. This approach not only enhances early detection but also provides a reliable and scalable solution for assisting medical professionals in clinical decision-making (Figure 2).

Step 1: Data Acquisition

The first step in the proposed system involves collecting cervical cell images from reliable and publicly available medical datasets, such as Pap smear image repositories. These datasets typically contain images representing different stages of cervical health, including normal, pre-

cancerous, and cancerous conditions. Proper labeling of the dataset is essential to ensure accurate supervised learning and classification.



**Figure 2: Proposed methodology for early-stage cervical cancer prediction using a transfer learning-based ResNet50 model**

### Step 2: Data Preprocessing

In this stage, the collected images undergo preprocessing to enhance their quality and make them suitable for deep learning analysis. Each image is resized to a standard dimension of  $224 \times 224$  pixels to match the input requirements of ResNet50. Pixel values are normalized to improve model convergence. Additionally, data augmentation techniques such as rotation, flipping, zooming, and noise reduction are applied to increase dataset diversity and reduce overfitting.

### Step 3: Feature Extraction Using ResNet50

The pre-processed images are then fed into a pre-trained ResNet50 model for deep feature extraction. The top classification layers of the network are removed, allowing the model to act as a powerful feature extractor. Its residual learning architecture helps capture complex spatial patterns and ensures efficient training by mitigating issues such as vanishing gradients. This step plays a crucial role in identifying subtle cellular abnormalities.

### Step 4: Classification Layer Design

After extracting features, a custom classification head is added to the base model. This includes a Global Average Pooling layer to reduce feature dimensions, followed by a fully connected dense layer with ReLU activation to learn non-linear patterns. A dropout layer is incorporated to prevent overfitting, and finally, a Softmax output layer is used to classify the images into predefined categories such as normal, pre-cancerous, and cancerous.

### Step 5: Model Training

The complete model is then trained using the labeled dataset. During training, the system learns to map extracted features to the correct class labels. The categorical cross-entropy loss function is used to measure prediction error, while the Adam optimizer is employed for efficient weight updates. Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure robust classification performance.

### Step 6: Fine-Tuning of the Model

To further improve performance, fine-tuning is applied by unfreezing the top layers of the pre-trained ResNet50 model. These layers are retrained using a low learning rate, allowing the network to adapt more effectively to domain-

specific features present in cervical cell images. This step enhances the model’s ability to detect early-stage abnormalities with higher precision.

Step 7: Prediction and Decision Module

In the final step, the trained model is used for prediction. A new cervical cell image is provided as input, which undergoes the same preprocessing steps before being passed through the network. The model outputs a probability distribution across different classes, and the class with the highest probability is selected as the final prediction. This module supports clinicians by providing fast and reliable diagnostic insights for early-stage cervical cancer detection.

4.2 Algorithm

Algorithm: Segmentation-Assisted Multilevel Ensemble Model

1. LOAD DATASET
  - Input: Cervical cell images dataset
  - Labels: Normal / Pre-cancerous / Cancerous
2. PREPROCESS DATA
  - FOR each image in dataset DO
    - Resize image to 224 x 224 pixels
    - Normalize pixel values (0 to 1)
    - Apply data augmentation:
      - Rotation
      - Flipping
      - Zooming
  - END FOR
3. SPLIT DATASET
  - Training set (70%)
  - Validation set (15%)
  - Test set (15%)
4. LOAD PRE-TRAINED MODEL
  - Import ResNet50 model
  - Weights: ImageNet
  - Exclude top (fully connected layers)
5. BUILD CUSTOM CLASSIFIER
  - Add Global Average Pooling layer
  - Add Dense layer (ReLU activation)
  - Add Dropout layer (rate = 0.5)
  - Add Output layer (Softmax activation for classification)
6. FREEZE BASE LAYERS
  - FOR each layer in ResNet50 base model DO
    - Set layer.trainable = FALSE
  - END FOR
7. COMPILE MODEL
  - Loss Function: Categorical Crossentropy
  - Optimizer: Adam
  - Metrics: Accuracy, Precision, Recall, F1-score
8. TRAIN MODEL

- FOR epoch = 1 to N DO
  - Train model on training set
  - Validate on validation set
  - Monitor loss and accuracy
- END FOR
- 9. FINE-TUNING
  - Unfreeze last few layers of ResNet50
  - Retrain model with low learning rate
- 10. EVALUATE MODEL
  - Test model on unseen test dataset
  - Compute:
    - Accuracy
    - Precision
    - Recall
    - F1-score
    - Confusion Matrix
- 11. PREDICTION
  - INPUT: New cervical cell image
    - Preprocess image
    - Pass through trained model
  - OUTPUT: Predicted class label
- END

4. PERFORMANCE EVALUATION

Precision, recall, accuracy, and F1-score are commonly used evaluation metrics for assessing classification model performance, each highlighting a different aspect of predictive capability. Accuracy represents the overall correctness of the model by measuring the proportion of correctly classified instances among all samples. Precision evaluates the reliability of positive predictions by determining how many predicted positives are actually correct, while recall (or sensitivity) measures the model’s ability to correctly identify actual positive cases. The F1-score combines precision and recall into a single metric using their harmonic mean, providing a balanced assessment that accounts for both false positives and false negatives. Together with additional measures such as specificity and sensitivity, these metrics offer a comprehensive evaluation of the model’s effectiveness in detecting cervical abnormalities. All these performance indicators are derived from the confusion matrix, which consists of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values.

Table 2. Performance evaluation metrics

Metric	Definition	Formulas
Precision	Positive predictive value	$Precision = TP / (TP + FP)$
Recall	True positive rate	$Recall = TP / (TP + FN)$

Accuracy	Overall accuracy	$Accuracy = (TP + TN) / (TP + TN + FP + FN)$
F1 score	Harmonic mean of precision and recall	$F1\ Score = 2 * (Precision * Recall) / (Precision + Recall)$

**5. RESULT AND ANALYSIS**

Figure 3 presents the sequential processing stages involved in analyzing cervical cancer-affected images. Initially, the

input image (a) represents the raw cervical sample captured for examination. In the next stage (b), contrast enhancement is applied to improve the visibility of important structural features, highlighting subtle variations in tissue texture and color that may indicate abnormalities. Finally, the segmented image (c) isolates the defective or potentially cancerous region, enabling precise identification of affected areas for further diagnostic evaluation and classification by the proposed model.

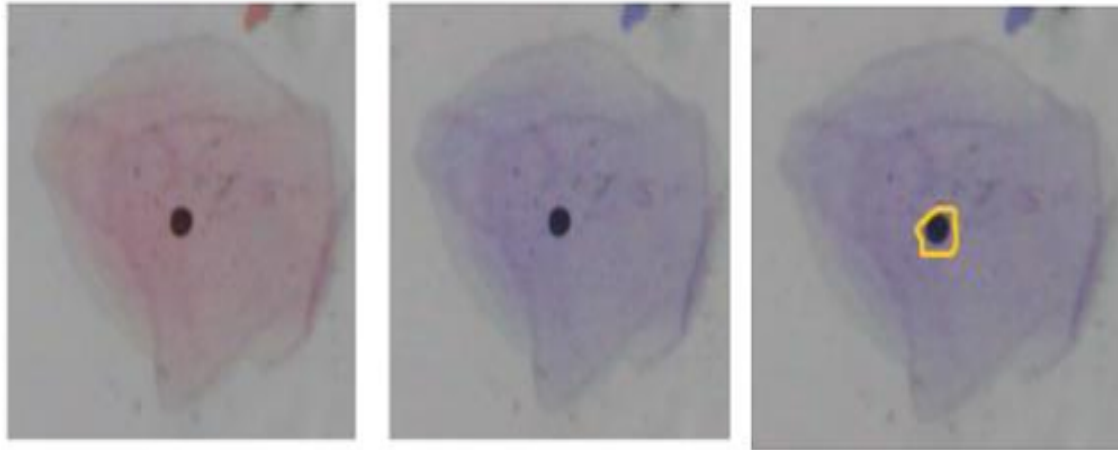
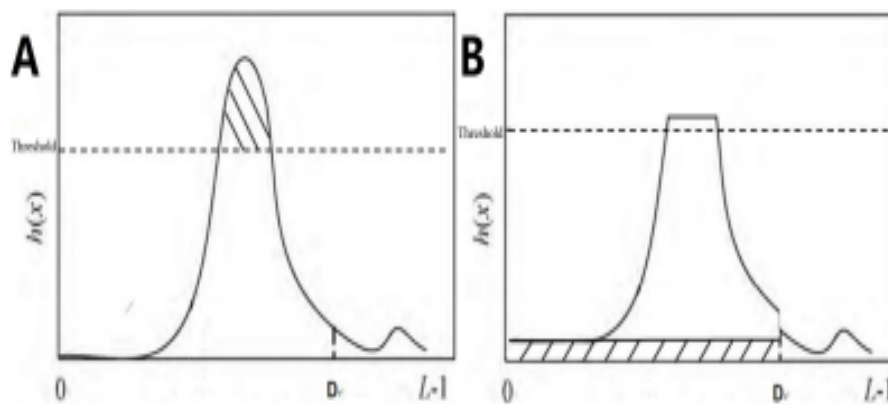


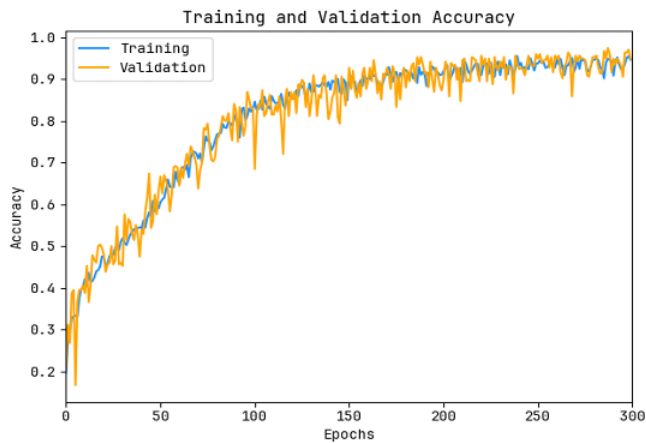
Figure 3. Output visualization of cervical cancer-affected images: (a) Original input image, (b) Contrast-enhanced image, and (c) Segmented defective region.



**Figure 4. Histogram before processing; (B) histogram after processing**

The figure 4 shows the comparison of image histograms before and after processing. (A) represents the histogram of the original image prior to enhancement, illustrating uneven

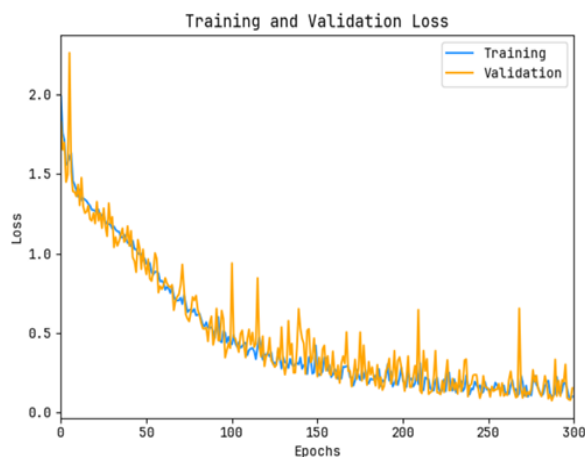
intensity distribution. (B) shows the histogram after processing, where intensity levels are more balanced, indicating improved contrast and better visual quality.



**Figure 5. Accuracy curve of proposed methodology**

Figure 5 illustrates the accuracy curve of the proposed model during the training and validation phases. The curve shows a steady increase in accuracy over successive epochs, indicating effective learning and convergence of the model. Both training and validation accuracies rise consistently and stabilize near the final epochs, demonstrating that the model generalizes well without significant overfitting. This consistent upward trend confirms the robustness of the proposed hybrid architecture in accurately classifying cervical precancer images.

Figure 6 presents the loss curve, depicting the reduction in training and validation loss as the model progresses through epochs. The loss decreases rapidly in the initial stages, showing fast learning, and gradually flattens out, indicating convergence. The close alignment between training and validation loss curves suggests that the model maintains good generalization with minimal overfitting. This stable and decreasing loss trend validates the efficiency of the model’s optimization process in achieving reliable performance for cervical precancer detection.



**Figure 6. Loss curve of proposed methodology**

The experimental results demonstrate a clear variation in performance across different classification models for cervical cancer prediction. The basic CNN model achieves an accuracy of 89.45%, with precision, recall, and F1-score values of 88.70%, 87.95%, and 88.32%, respectively. This indicates that while CNN is capable of extracting spatial features, its relatively shallow architecture limits its ability to capture more complex patterns in cervical cell images. Similarly, the Support Vector Machine shows comparatively lower performance, with an accuracy of 85.20%, reflecting its dependence on handcrafted features and limited capability in handling high-dimensional image data.

**Table 2. Performance comparison of the proposed approach with existing models**

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN (Basic)	89.45	88.70	87.95	88.32
Support Vector Machine	85.20	84.75	83.90	84.32
Random Forest	91.10	90.25	89.80	90.02
K-Nearest Neighbors	83.75	82.90	82.10	82.50
ResNet50 (Proposed)	96.85	96.20	96.00	96.10

The Random Forest model performs better than both CNN and SVM, achieving an accuracy of 91.10% along with improved precision (90.25%), recall (89.80%), and F1-score (90.02%). This improvement can be attributed to its ensemble nature, which combines multiple decision trees to enhance generalization and reduce overfitting. In contrast, the K-Nearest Neighbors algorithm records the lowest performance among all models, with an accuracy of 83.75%, as it is sensitive to noise and struggles with large-scale image datasets (Table 2).

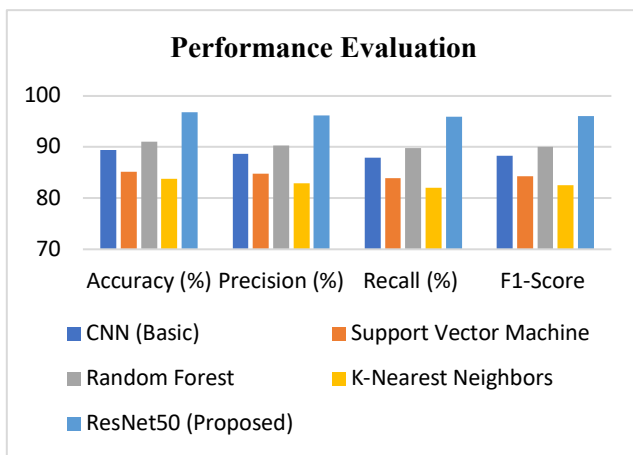


Figure 7. Performance comparison of the proposed approach with existing models.

The proposed ResNet50 model significantly outperforms all other approaches, achieving the highest accuracy of 96.85%, along with precision of 96.20%, recall of 96.00%, and F1-score of 96.10%. This superior performance is primarily due to the deep residual learning mechanism, which allows the network to learn complex and hierarchical features effectively. The use of transfer learning further enhances its capability by leveraging pre-trained knowledge, making it highly suitable for medical image classification tasks with limited data.

The comparative analysis clearly indicates that deep learning-based approaches, particularly the proposed ResNet50 model, provide more reliable and accurate predictions than traditional machine learning techniques. The balanced improvement across all evaluation metrics suggests that the model not only achieves high accuracy but also maintains consistency in correctly identifying both positive and negative cases. This makes the proposed system a robust and efficient solution for early-stage cervical cancer detection, with significant potential for real-world clinical applications (Figure 7).

## 6. CONCLUSION

The study presented a robust framework for early-stage cervical cancer prediction using a transfer learning-based deep neural network built upon the ResNet50 model. By leveraging pre-trained knowledge and fine-tuning it on cervical cell image datasets, the proposed approach effectively captured complex visual patterns associated with precancerous conditions. The integration of preprocessing techniques and a customized classification layer further enhanced the model's ability to generalize across varying image characteristics. This methodology addresses key limitations of traditional screening approaches by offering a more automated, consistent, and scalable solution for early detection. The experimental

results demonstrate that the proposed ResNet50-based model significantly outperforms conventional machine learning and basic deep learning approaches. Specifically, the model achieved an accuracy of 96.85%, precision of 96.20%, recall of 96.00%, and an F1-score of 96.10%, surpassing baseline models such as CNN (89.45% accuracy), Support Vector Machine (85.20%), Random Forest (91.10%), and K-Nearest Neighbors (83.75%). These findings highlight the effectiveness of transfer learning in improving diagnostic performance, particularly in medical imaging scenarios with limited data. Overall, the proposed system shows strong potential for assisting clinicians in early-stage cervical cancer diagnosis, thereby contributing to improved patient outcomes and advancing intelligent healthcare systems.

## REFERENCE

- [1] B. Harangi, E. Csillag, and A. Hajdu, "Pixel-wise segmentation of cells in digitized Pap smear images," *Nature Scientific Reports*, vol. 14, no. 3, pp. 1121–1130, 2024. ISSN: 2045-2322.
- [2] J. Ji, W. Chen, and L. Zhang, "Automated cervical cell segmentation using deep ensemble methods," *BMC Medical Imaging*, vol. 23, no. 5, pp. 67–79, 2023. BioMed Central Ltd. ISSN: 1471-2342.
- [3] A. Manna, P. Mitra, and D. Bandyopadhyay, "A fuzzy rank-based ensemble of CNN models for cervical cell classification," *PLOS One*, vol. 16, no. 12, e0260021, pp. 1–14, 2021.
- [4] H. A. Sarhangi and N. Khadem, "Deep learning techniques for cervical cancer diagnosis A comprehensive review," *Computer Methods and Programs in Biomedicine*, vol. 245, pp. 107764–107781, 2024.
- [5] S. L. Tan, K. Y. Lee, and M. T. Goh, "Comparison of deep transfer learning models for Pap smear classification," *Springer Nature Computer Science*, vol. 5, pp. 144–158, 2024.
- [6] J. Gangrade, A. Sharma, and P. K. Singh, "A deep ensemble learning approach for squamous cell classification in Pap smear images," *Nature Biomedical Engineering*, vol. 9, no. 2, pp. 121–135, 2025. ISSN: 2157-846X.
- [7] B. S. Deo and R. Patel, "A Pap smear-based cervical cancer classification method using Transformer hybrids," *arXiv preprint, arXiv:2308.04219*, pp. 1–10, 2023.
- [8] M. M. Ali and A. Rahman, "Machine learning-based statistical analysis for early-stage cervical cancer detection," *Computerized Medical Imaging and Graphics*, vol. 93, pp. 102019–102031, 2021.
- [9] J. Su, W. Liu, and T. Zhang, "Cervical cancer prediction using machine learning models with clinical

- features,” *Nature Communications Medicine*, vol. 4, no. 7, pp. 211–224, 2025.
- [10] D. Kupas, L. Hansen, and A. Larsen, “Annotated Pap cell images and smear slices for the Herlev dataset: Extended dataset description and benchmark,” *Nature Scientific Data*, vol. 11, no. 2, pp. 455–470, 2024.
- [11] SIPaKMeD Dataset, “SIPaKMeD: A new dataset for cervical cell classification,” *Kaggle Public Repository*, 2024. Available: <https://www.kaggle.com/datasets/paultimothymooney/sipa-kmed-cervical-cell-dataset>
- [12] W. William, A. Ware, A. H. Basaza-Ejjiri, and J. Obungoloch, “A Pap-smear analysis tool (PAT) for the detection of cervical cancer from Pap smear images,” *Biomedical Engineering Online*, vol. 18, pp. 1–22, 2019.
- [13] P. Wang, J. Wang, Y. Li, L. Li, and H. Zhang, “Adaptive pruning of transfer learned deep convolutional neural network for classification of cervical Pap smear images,” *IEEE Access*, vol. 8, pp. 50674–50683, 2020.
- [14] E. Hussain, L. B. Mahanta, C. R. Das, and R. K. Talukdar, “A comprehensive study on the multi-class cervical cancer diagnostic prediction on Pap smear images using a fusion-based decision from ensemble deep convolutional neural network,” *Tissue and Cell*, vol. 65, p. 101347, 2020.
- [15] D. Riana, Y. Ramdhani, and T. P. Rizki, “Improving hierarchical decision approach for single image classification of Pap smear,” *International Journal of Electrical and Computer Engineering*, vol. 8, no. 6, p. 5415, 2018.
- [16] W. Liu, Y. Zhang, J. He, and C. Li, “CVM-Cervix: A hybrid cervical Pap smear image classification framework using CNN, visual transformer, and multilayer perceptron,” *Pattern Recognition*, vol. 130, p. 108829, 2022.
- [17] M. A. Mohammed, F. Abdurahman, and Y. A. Ayalew, “Single-cell conventional Pap smear image classification using pre-trained deep neural network architectures,” *BMC Biomedical Engineering*, vol. 3, no. 1, p. 11, 2021. -8.
- [18] S. Fekri-Ershad, “Pap smear classification using combination of global significant value, texture statistical features and time series features,” *Multimedia Tools and Applications*, vol. 78, no. 22, pp. 31121–31136, 2019.
- [19] R. Gupta, A. Sarwar, and V. Sharma, “Screening of cervical cancer by artificial intelligence-based analysis of digitized Papanicolaou-smear images,” *International Journal of Contemporary Medical Research*, vol. 4, no. 5, pp. 2454–7379, 2017.
- [20] D. Selvathi, W. R. Sharmila, and P. S. Sankari, “Advanced computational intelligence techniques-based computer-aided diagnosis system for cervical cancer detection using Pap smear images,” in *Classification in BioApps: Automation of Decision Making, Lecture Notes in Computational Vision and Biomechanics*, vol. 26, Springer, Cham, pp. 295–322, 2018..
- [21] V. Kumararaja and K. Deepa, “Pap smear image classification to predict urinary cancer using artificial neural networks,” *Annals of the Romanian Society for Cell Biology*, vol. 25, no. 2, pp. 1092–1098, 2021. ISSN: 1583-6258.
- [22] C. W. Wang, Y. C. Lin, W. H. Hsu, and S. H. Huang, “Artificial intelligence-assisted fast screening of cervical high-grade squamous intraepithelial lesion and squamous cell carcinoma: Diagnosis and treatment planning,” *Scientific Reports*, vol. 11, no. 1, p. 16244, 2021.
- [23] P. V. Mulmule, R. D. Kanphade, and D. M. Dhane, “Artificial-intelligence-assisted cervical dysplasia detection using Papanicolaou smear images,” *The Visual Computer*, vol. 39, pp. 1–12, 2022.
- [24] P. Wang, L. Wang, Y. Li, Q. Song, S. Lv, and X. Hu, “Automatic cell nuclei segmentation and classification of cervical Pap smear images,” *Biomedical Signal Processing and Control*, vol. 48, pp. 93–103, 2019.
- [25] Y. R. Park, Y. J. Kim, W. Ju, K. Nam, S. Kim, and K. G. Kim, “Comparison of machine and deep learning for the classification of cervical cancer based on cervicography images,” *Scientific Reports*, vol. 11, no. 1, pp. 1–11, 2021.
- [26] F. B. M. Suah, “Preparation and characterization of a novel co(II) optode based on polymer inclusion membrane,” *Analytical Chemistry Research*, vol. 12, pp. 40–46, 2017.
- [27] T. Xu, H. Zhang, C. Xin et al., “Multi-feature based benchmark for cervical dysplasia classification evaluation,” *Analytical Chemistry Research*, vol. 63, pp. 468–475, 2017.
- [28] K. P. Battula and B. S. Chandana, “Deep learning based cervical cancer classification and segmentation from Pap smear images using an EfficientNet,” *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 13, no. 9, pp. 899–908, 2022.